Aircraft Analysis from Aviation Accident Data.

Introduction

Our company is entering the aviation industry, and we need to make smart choices to keep risks low. This project uses Aviation Accident data from the U.S. National Transportation Safety Board (NTSB) to help us make good buying decisions.

I will do this by carefully looking at, cleaning, and studying the data. The information I will find will give clear advice to the head of our new aviation department. This advice will help pick aircraft that are safer, allowing our company to start this new business with a stronger and more secure beginning.

Data Understanding

This project relies on Aviation Accident data from Kaggle, originally from the U.S. National Transportation Safety Board (NTSB). For full project context and key questions, refer to the README.

1. Data Exploration

With the project clearly explained, i will now load and explore the dataset to understand its structure, size, and contents.

```
# Import relevant libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

plt.style.available
plt.style.use('seaborn-darkgrid')
```

Next is Loading the dataset and previewing the first 5 and last 5 records

```
# Load the aviation dataset
df = pd.read_csv('Data/AviationData.csv', encoding = 'latin1',
low_memory = False)

# Display the first 5 rows
df.head()
```

```
         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24
1  20001218X45447           Accident      LAX94LA336  1962-07-19
```

```
2  20061025X01555         Accident      NYC07LA005  1974-08-30
3  20001218X45448         Accident      LAX96LA321  1977-06-19
4  20041105X01764         Accident      CHI79FA064  1979-08-02

          Location        Country   Latitude   Longitude Airport.Code
\
0  MOOSE CREEK, ID  United States        NaN         NaN          NaN

1   BRIDGEPORT, CA  United States        NaN         NaN          NaN

2    Saltville, VA  United States  36.922223  -81.878056          NaN

3       EUREKA, CA  United States        NaN         NaN          NaN

4       Canton, OH  United States        NaN         NaN          NaN


  Airport.Name  ... Purpose.of.flight Air.carrier Total.Fatal.Injuries
\
0          NaN  ...          Personal         NaN                  2.0

1          NaN  ...          Personal         NaN                  4.0

2          NaN  ...          Personal         NaN                  3.0

3          NaN  ...          Personal         NaN                  2.0

4          NaN  ...          Personal         NaN                  1.0


  Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
0                    0.0                  0.0             0.0
1                    0.0                  0.0             0.0
2                    NaN                  NaN             NaN
3                    0.0                  0.0             0.0
4                    2.0                  NaN             0.0

  Weather.Condition  Broad.phase.of.flight   Report.Status
Publication.Date
0               UNK                 Cruise  Probable Cause
NaN
1               UNK                Unknown  Probable Cause       19-
09-1996
2               IMC                 Cruise  Probable Cause       26-
02-2007
3               IMC                 Cruise  Probable Cause       12-
09-2000
4               VMC               Approach  Probable Cause       16-
04-1980

[5 rows x 31 columns]
```

```python
# Check the summary of the dataset to see the number of rows, columns,
data types, and any missing values.


df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      88889 non-null  object 
 2   Accident.Number         88889 non-null  object 
 3   Event.Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Latitude                34382 non-null  object 
 7   Longitude               34373 non-null  object 
 8   Airport.Code            50249 non-null  object 
 9   Airport.Name            52790 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87572 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81812 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82508 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

```python
# Generate  descriptive statistics to get an overview of the
distributions and general characteristics of the data in the cell
df.describe()
```

```
       Number.of.Engines  Total.Fatal.Injuries  Total.Serious.Injuries
\
count       82805.000000          77488.000000            76379.000000

mean            1.146585              0.647855                0.279881

std             0.446510              5.485960                1.544084

min             0.000000              0.000000                0.000000

25%             1.000000              0.000000                0.000000

50%             1.000000              0.000000                0.000000

75%             1.000000              0.000000                0.000000

max             8.000000            349.000000              161.000000


       Total.Minor.Injuries  Total.Uninjured
count          76956.000000     82977.000000
mean               0.357061         5.325440
std                2.235625        27.913634
min                0.000000         0.000000
25%                0.000000         0.000000
50%                0.000000         1.000000
75%                0.000000         2.000000
max              380.000000       699.000000
```

```python
# Explore the unique values in each column of our dataset
print("\nNumber of unique values in each column:")
df.nunique()
```

```
Number of unique values in each column:

Event.Id                  87951
Investigation.Type            2
Accident.Number           88863
Event.Date                14782
Location                  27758
Country                     219
Latitude                  25589
Longitude                 27154
Airport.Code              10375
Airport.Name              24871
Injury.Severity             109
Aircraft.damage               4
Aircraft.Category            15
Registration.Number       79105
Make                       8237
```

```
Model                      12318
Amateur.Built                  2
Number.of.Engines              7
Engine.Type                   13
FAR.Description               31
Schedule                       3
Purpose.of.flight             26
Air.carrier                13590
Total.Fatal.Injuries         125
Total.Serious.Injuries        50
Total.Minor.Injuries          57
Total.Uninjured              379
Weather.Condition              4
Broad.phase.of.flight         12
Report.Status              17075
Publication.Date            2924
dtype: int64
```

```python
# Check the datatypes in each column
df.dtypes
```

```
Event.Id                    object
Investigation.Type          object
Accident.Number             object
Event.Date                  object
Location                    object
Country                     object
Latitude                    object
Longitude                   object
Airport.Code                object
Airport.Name                object
Injury.Severity             object
Aircraft.damage             object
Aircraft.Category           object
Registration.Number         object
Make                        object
Model                       object
Amateur.Built               object
Number.of.Engines          float64
Engine.Type                 object
FAR.Description             object
Schedule                    object
Purpose.of.flight           object
Air.carrier                 object
Total.Fatal.Injuries       float64
Total.Serious.Injuries     float64
Total.Minor.Injuries       float64
Total.Uninjured            float64
Weather.Condition           object
Broad.phase.of.flight       object
```

```
Report.Status                  object
Publication.Date               object
dtype: object

# Check for missing values
df.isnull().sum()

# Calculate the percentage of missing values per column
null_percent = (df.isnull().sum() / len(df)) * 100

# Sort the columns from highest percentage of missing values to
lowest.
null_percent.sort_values(ascending = False)

Schedule                      85.845268
Air.carrier                   81.271023
FAR.Description               63.974170
Aircraft.Category             63.677170
Longitude                     61.330423
Latitude                      61.320298
Airport.Code                  43.469946
Airport.Name                  40.611324
Broad.phase.of.flight         30.560587
Publication.Date              15.492356
Total.Serious.Injuries        14.073732
Total.Minor.Injuries          13.424608
Total.Fatal.Injuries          12.826109
Engine.Type                    7.961615
Report.Status                  7.178616
Purpose.of.flight              6.965991
Number.of.Engines              6.844491
Total.Uninjured                6.650992
Weather.Condition              5.053494
Aircraft.damage                3.593246
Registration.Number            1.481623
Injury.Severity                1.124999
Country                        0.254250
Amateur.Built                  0.114750
Model                          0.103500
Make                           0.070875
Location                       0.058500
Event.Date                     0.000000
Accident.Number                0.000000
Investigation.Type             0.000000
Event.Id                       0.000000
dtype: float64

# Check for duplicates in the dataset
df.duplicated().sum()
```

```
0
```

Conclusion on Data Exploration

The dataset contains a mix of categorical and numerical features related to aviation accidents. No duplicate records were found, but several columns contain missing values and will require cleaning. I will focus on selecting relevant columns for deeper analysis, with the goal of identifying patterns and risk factors that can support safer aircraft acquisition decisions.

2. Data Cleaning

Data cleaning is a crucial step to ensure the quality and reliability of the analysis. In this section i will handle missing values and correct inconsistent data formats. Clean data will help produce accurate insights that support better decision-making.

First is to standardize Column Names since some use dot like, `Event.Id`, `Total.Fatal.Injuries`. Let's clean them.

```
# Let's check the column names here
df.columns

Index(['Event.Id', 'Investigation.Type', 'Accident.Number',
'Event.Date',
       'Location', 'Country', 'Latitude', 'Longitude', 'Airport.Code',
       'Airport.Name', 'Injury.Severity', 'Aircraft.damage',
       'Aircraft.Category', 'Registration.Number', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type',
'FAR.Description',
       'Schedule', 'Purpose.of.flight', 'Air.carrier',
'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries',
'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')

# Cleaning now column names
df.columns = df.columns.str.capitalize().str.replace('.', '_', regex =
False)
df.columns

Index(['Event_id', 'Investigation_type', 'Accident_number',
'Event_date',
       'Location', 'Country', 'Latitude', 'Longitude', 'Airport_code',
       'Airport_name', 'Injury_severity', 'Aircraft_damage',
       'Aircraft_category', 'Registration_number', 'Make', 'Model',
       'Amateur_built', 'Number_of_engines', 'Engine_type',
'Far_description',
       'Schedule', 'Purpose_of_flight', 'Air_carrier',
'Total_fatal_injuries',
```

```
       'Total_serious_injuries', 'Total_minor_injuries',
'Total_uninjured',
       'Weather_condition', 'Broad_phase_of_flight', 'Report_status',
       'Publication_date'],
      dtype='object')

# Check each column dtypes
df.dtypes

Event_id                      object
Investigation_type            object
Accident_number               object
Event_date                    object
Location                      object
Country                       object
Latitude                      object
Longitude                     object
Airport_code                  object
Airport_name                  object
Injury_severity               object
Aircraft_damage               object
Aircraft_category             object
Registration_number           object
Make                          object
Model                         object
Amateur_built                 object
Number_of_engines            float64
Engine_type                   object
Far_description               object
Schedule                      object
Purpose_of_flight             object
Air_carrier                   object
Total_fatal_injuries         float64
Total_serious_injuries       float64
Total_minor_injuries         float64
Total_uninjured              float64
Weather_condition             object
Broad_phase_of_flight         object
Report_status                 object
Publication_date              object
dtype: object
```

Examining the columns, we see that the `Event_date` column is currently stored as an object data type. We convert it into a proper datetime format using the `pd.to_datetime()` function to enable time-based analysis.

```
# Convert Event_date to datetime
df['Event_date'] = pd.to_datetime(df['Event_date'], errors = 'coerce')
```

```
# Check for dates not converted
print(f"The number not converted is :
{df['Event_date'].isnull().sum()}")

# Extract Year to help in analysis
df['Year'] = df['Event_date'].dt.year

# Extract Month also
df['Month'] = df['Event_date'].dt.month

print(df[['Event_date', 'Year', 'Month']].head())
```

```
The number not converted is : 0
  Event_date  Year  Month
0 1948-10-24  1948     10
1 1962-07-19  1962      7
2 1974-08-30  1974      8
3 1977-06-19  1977      6
4 1979-08-02  1979      8
```

Since injury columns have missing values, they likely indicate no injuries occurred or unreported incidents and they are `float64` and might have NaNs. I will fill NaNs with 0 and convert injury columns to integers.

```
# Columns to clean and convert to integers
injury_cols = ['Total_fatal_injuries', 'Total_serious_injuries',
'Total_minor_injuries', 'Total_uninjured']

for col in injury_cols:
    # convert to numeric
    df[col] = pd.to_numeric(df[col], errors = 'coerce')
    # Fill missing values with 0
    df[col].fillna(0, inplace = True)
    # Convert to integer
    df[col] = df[col].astype(int)

print("\nInjury columns after  conversion")
print(df[injury_cols].info())
```

```
Injury columns after  conversion
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 4 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Total_fatal_injuries    88889 non-null  int32
 1   Total_serious_injuries  88889 non-null  int32
 2   Total_minor_injuries    88889 non-null  int32
```

```
 3   Total_uninjured         88889 non-null  int32
dtypes: int32(4)
memory usage: 1.4 MB
None
```

```python
# Check missing values in each column again
df.isnull().sum()
```

```
Event_id                      0
Investigation_type            0
Accident_number               0
Event_date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport_code              38640
Airport_name              36099
Injury_severity            1000
Aircraft_damage            3194
Aircraft_category         56602
Registration_number        1317
Make                         63
Model                        92
Amateur_built               102
Number_of_engines          6084
Engine_type                7077
Far_description           56866
Schedule                  76307
Purpose_of_flight          6192
Air_carrier               72241
Total_fatal_injuries          0
Total_serious_injuries        0
Total_minor_injuries          0
Total_uninjured               0
Weather_condition          4492
Broad_phase_of_flight     27165
Report_status              6381
Publication_date          13771
Year                          0
Month                         0
dtype: int64
```

We now handle the `Make` and `Model` columns since they define our aicraft type hence there will be need to combine them. Also potential missing values will be dealt with.

```python
# To minimiza errors during concatenation i convert the columns to string
df['Make'] = df['Make'].astype(str)
```

```python
df['Model'] = df['Model'].astype(str)
# Combine 'Make' and 'Model' into a new 'Aircraft_Type' column
df['Aircraft_Type'] = df['Make'] + ' ' + df['Model']
# Replace 'nan' string values that result from missing data in
original Make/Model
df['Aircraft_Type'] = df['Aircraft_Type'].replace('nan nan', np.nan)
# Drop rows where 'Aircraft_Type' is still NaN
df.dropna(subset = ['Aircraft_Type'], inplace = True)

print(f"DataFrame shape after dropping missing Aircraft_Type:
{df.shape}")

# Check unique values for `Aircraft_Type`
print(f"Number of unique values: {df['Aircraft_Type'].nunique()}")
print(df['Aircraft_Type'].value_counts().head(10))
```

```
DataFrame shape after dropping missing Aircraft_Type: (88846, 34)
Number of unique values: 20182
Cessna 152         2168
Cessna 172         1254
Cessna 172N         996
Piper PA-28-140     812
Cessna 150          716
Cessna 172M         667
Cessna 172P         597
Piper PA-18         539
Cessna 150M         539
Piper PA-28-161     502
Name: Aircraft_Type, dtype: int64
```

Next we are going to clean `Weather_Condition` and `Broad_phase_of_flight`since they are categorical and important. We'll check the unique values and consider standardization.

```python
# Check 'Weather_Condition'
df['Weather_condition'].value_counts(dropna=False)

df['Weather_condition'] = df['Weather_condition'].replace({'UNK':
'Unknown', 'Unk': 'Unknown'})
df['Weather_condition'].fillna('Unknown', inplace=True)

print(df['Weather_condition'].value_counts(dropna=False))
```

```
VMC        77295
IMC         5976
Unknown     5575
Name: Weather_condition, dtype: int64
```

```python
# Check 'Broad_phase_of_flight'
df['Broad_phase_of_flight'].value_counts(dropna=False)
```

```
df['Broad_phase_of_flight'] =
df['Broad_phase_of_flight'].replace({'Unk': 'Unknown'})
df['Broad_phase_of_flight'].fillna('Unknown', inplace=True) # Fill any
actual NaNs

print(df['Broad_phase_of_flight'].value_counts(dropna=False))
```

```
Unknown        27670
Landing        15428
Takeoff        12493
Cruise         10269
Maneuvering     8144
Approach        6546
Climb           2034
Taxi            1958
Descent         1887
Go-around       1353
Standing         945
Other            119
Name: Broad_phase_of_flight, dtype: int64
```

Now i will drop the original `Make` and `Model` columns as they are now combined into `Aircraft_Type` column. Also considering dropping other columns that are not directly used or have too many NaNs for this analysis.

```
# List of columns to drop.
columns_drop = [
    'Make', 'Model','Accident_number', 'Investigation_type',
'Event_id', 'Latitude', 'Longitude', 'Airport_code', 'Airport_name',
    'Publication_date',  'Report_status', 'Far_description',
'Aircraft_damage', 'Injury_severity','Aircraft_category',
'Air_carrier',
    'Engine_type', 'Schedule', 'Registration_number', 'Amateur_built']
# drop the columns
df.drop(columns=columns_drop, inplace=True, errors='ignore')

print(f"Dataframe after dropped columns : {df.shape}")
```

```
Dataframe after dropped columns : (88846, 14)
```

```
# Check for missing values again
df.isnull().sum()
```

```
Event_date                0
Location                 52
Country                 225
Number_of_engines      6043
Purpose_of_flight      6153
Total_fatal_injuries      0
```

```
Total_serious_injuries      0
Total_minor_injuries        0
Total_uninjured             0
Weather_condition           0
Broad_phase_of_flight       0
Year                        0
Month                       0
Aircraft_Type               0
dtype: int64
```

Looking at the missing values above the `Number_of_engines` column still has missing values. Knowing if single-engine aircraft are riskier than multi-engine ones could be a key insight for your company. So i will proceed to clean the column.

```
# Clean the column
df['Number_of_engines'].value_counts(dropna=False)

# For number of engines, mode  makes sense as 1.0 and 2.0 are frequent
mode_engines = df['Number_of_engines'].mode()[0] # Gets the most
frequent value
# Convert to int after filling NaNs
df['Number_of_engines'].fillna(mode_engines, inplace=True)
df['Number_of_engines'] = df['Number_of_engines'].astype(int)

print(df['Number_of_engines'].value_counts(dropna=False))

1    75624
2    11078
0     1226
3      483
4      431
8        3
6        1
Name: Number_of_engines, dtype: int64
```

Next we look at the `Purpose_of_flight` column. It has several missing values but it can provide insights if commercial passenger flights have different risk than personal flights.

```
# Clean Purpose_of_flight
df['Purpose_of_flight'].value_counts(dropna = False)
# Fill with unknown
df['Purpose_of_flight'].fillna('Unknown', inplace=True)

print("\n After Cleaning 'Purpose_of_flight' ")
print(df['Purpose_of_flight'].value_counts(dropna=False))


 After Cleaning 'Purpose_of_flight'
Personal                         49446
```

```
Unknown                        12953
Instructional                  10601
Aerial Application              4712
Business                        4018
Positioning                     1646
Other Work Use                  1264
Ferry                            812
Aerial Observation               794
Public Aircraft                  720
Executive/corporate              553
Flight Test                      405
Skydiving                        182
External Load                    123
Public Aircraft - Federal        105
Banner Tow                       101
Air Race show                     99
Public Aircraft - Local           74
Public Aircraft - State           64
Air Race/show                     59
Glider Tow                        53
Firefighting                      40
Air Drop                          11
ASHO                               6
PUBS                               4
PUBL                               1
Name: Purpose_of_flight, dtype: int64
```

```
# Lets run the missing value check again to see columns that have issues
df.isnull().sum()
```

```
Event_date                  0
Location                   52
Country                   225
Number_of_engines           0
Purpose_of_flight           0
Total_fatal_injuries        0
Total_serious_injuries      0
Total_minor_injuries        0
Total_uninjured             0
Weather_condition           0
Broad_phase_of_flight       0
Year                        0
Month                       0
Aircraft_Type               0
dtype: int64
```

Lastly the `Location` and `Country` columns still has missing value. I will consider dropping the rows with missing value to ensure I'm working with records where the location and country are definitively known, which will be important for geographical filtering.

```python
# Lets check the value_counts in the two columns
df[['Location', 'Country']].isnull().sum()

# Drop rows where 'Location' or 'Country' is missing
df.dropna(subset=['Location', 'Country'], inplace=True)

# Confirm if the missing values are still there
print(df[['Location', 'Country']].isnull().sum())
```

```
Location    0
Country     0
dtype: int64
```

```python
#Final check on missing values
df.isnull().sum()
```

```
Event_date                0
Location                  0
Country                   0
Number_of_engines         0
Purpose_of_flight         0
Total_fatal_injuries      0
Total_serious_injuries    0
Total_minor_injuries      0
Total_uninjured           0
Weather_condition         0
Broad_phase_of_flight     0
Year                      0
Month                     0
Aircraft_Type             0
dtype: int64
```

```python
# Save the modified DataFrame to a new Excel file
df.to_excel("clean_data.xlsx", index=False)
```

Conclusion

The initial `Aviation Accident` dataset has been thoroughly cleaned and prepared. Key steps included standardizing column names, converting data types e.g dates to datetime, injuries columns to integers and creating a combined `Aircraft_Type` column. Importantly, all missing values in critical columns have been addressed, resulting in a dataset of 88,570 entries across 14 relevant columns. This cleaned data is now fully ready for Exploratory Data Analysis to identify low-risk aircraft.

Exploratory Data Analysis

Having cleaned the dataset, the next phase is Exploratory Data Analysis (EDA). EDA is an essential step in any data project, acting as a detective phase where we investigate the dataset's main characteristics and uncover patterns often with visual methods.

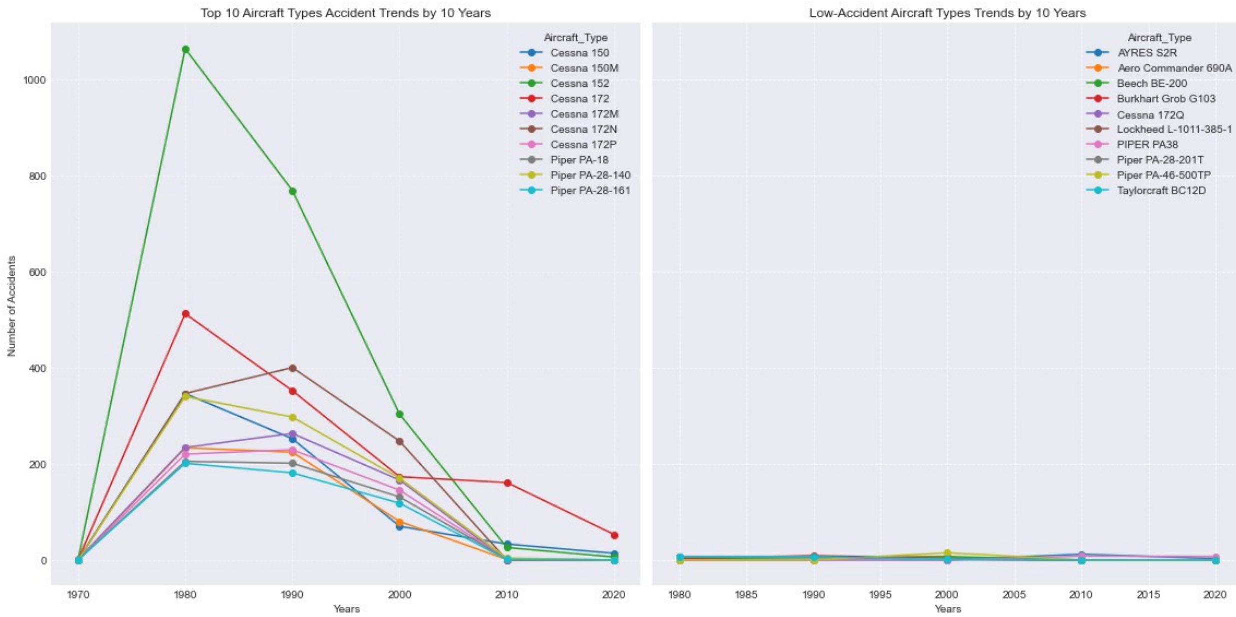
For this project, EDA will enable us to visually and statistically explore accident frequencies, fatality counts, and the influence of various factors like aircraft type, weather, and flight phase to directly address our company's goal of identifying the lowest-risk aircraft for acquisition.

Overall Accident Trends

We begin by looking at the number of accidents caused by aicraft types with a spacing of 10 year interval.

```
# Create column for 10-year intervals
df['Years_10'] = (df['Year'] // 10) * 10

# Find top 10 aircraft counts then groupby and pivot
top_10_aircraft = df['Aircraft_Type'].value_counts().head(10).index
df_top = df[df['Aircraft_Type'].isin(top_10_aircraft)].copy()
accidents_top_10 = df_top.groupby(['Years_10',
'Aircraft_Type']).size().reset_index(name = 'Accident_Count')
pivot_top_10 = accidents_top_10.pivot(index='Years_10', columns =
'Aircraft_Type', values = 'Accident_Count').fillna(0)

# Find Low-accident aircraft counts then groupby and pivot Low-
accident aircraft
aircraft_counts = df['Aircraft_Type'].value_counts()
low_aircraft = aircraft_counts[(aircraft_counts >= 5) &
(aircraft_counts <= 15)].head(10).index
df_low = df[df['Aircraft_Type'].isin(low_aircraft)]
accidents_low = df_low.groupby(['Years_10',
'Aircraft_Type']).size().reset_index(name = 'Accident_Count')
pivot_low = accidents_low.pivot(index = 'Years_10', columns =
'Aircraft_Type', values = 'Accident_Count').fillna(0)

# Plotting
fig, axes = plt.subplots(1, 2, figsize = (16, 8), sharey = True)

# Plotting the top 10
pivot_top_10.plot(ax = axes[0], kind = 'line', marker = 'o')
axes[0].set_title("Top 10 Aircraft Types Accident Trends by 10 Years")
axes[0].set_xlabel("Years")
axes[0].set_ylabel("Number of Accidents")
axes[0].grid(True, linestyle = '--', alpha = 0.5)

# Plot low-accident
pivot_low.plot(ax = axes[1], kind = 'line', marker = 'o')
axes[1].set_title("Low-Accident Aircraft Types Trends by 10 Years")
axes[1].set_xlabel("Years")
axes[1].grid(True, linestyle = '--', alpha = 0.8)

# Layout and show
plt.tight_layout()
```

```
plt.savefig('Images/Trends.png', dpi=300, bbox_inches='tight') # saves visual to image folder of my project
plt.show()
```

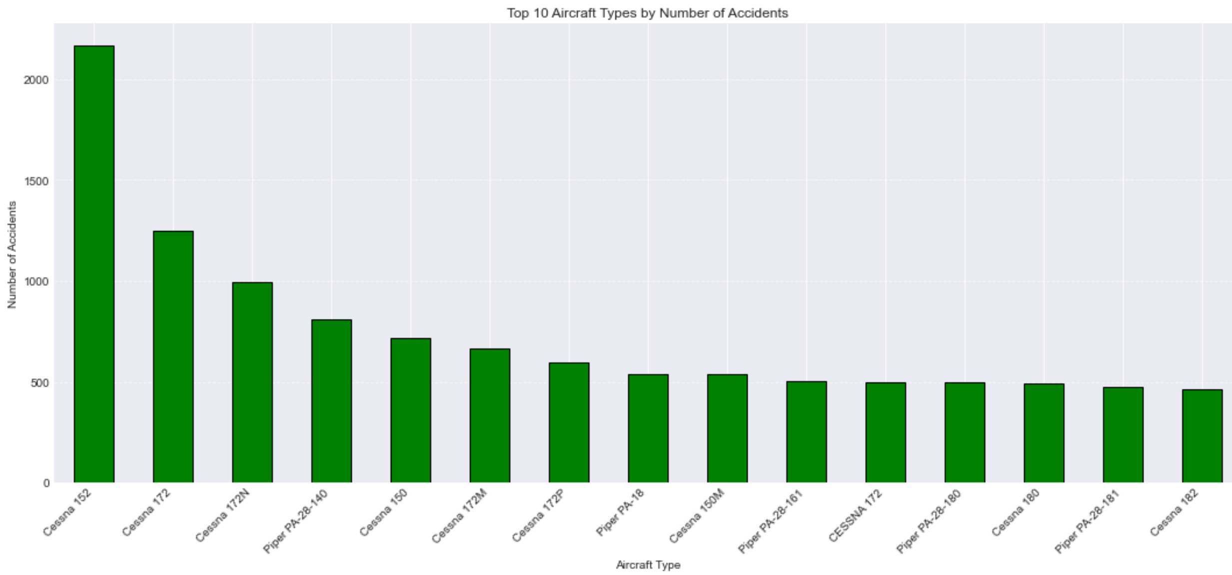


The accident trend analysis reveals that aircraft like Cessna 152, Cessna 172, and Piper PA-28-140 have high accident counts .In contrast, aircraft such as Piper PA-34, Taylorcraft DCO-65, and Boeing 737-222 show flat, low accident trends.

Aicraft types with high number of accidents

A bar chart of aircraft type vs number of accidents will help directly answer: Which aircraft types have been involved in the most accidents overall?

```
# Count total accidents per aircraft type
aircraft_accidents = df['Aircraft_Type'].value_counts().head(15)

# Plot
plt.figure(figsize =  (15, 7))
aircraft_accidents.plot(kind = 'bar', color = 'green', edgecolor = 'black')
plt.title('Top 10 Aircraft Types by Number of Accidents')
plt.xlabel('Aircraft Type')
plt.ylabel('Number of Accidents')
plt.xticks(rotation = 45, ha = 'right')
plt.grid(axis = 'y', linestyle = '--', alpha = 0.7)
plt.tight_layout()
plt.savefig('Images/Accidents.png', dpi=300, bbox_inches='tight') # saves visual to image folder of my project
plt.show()
```

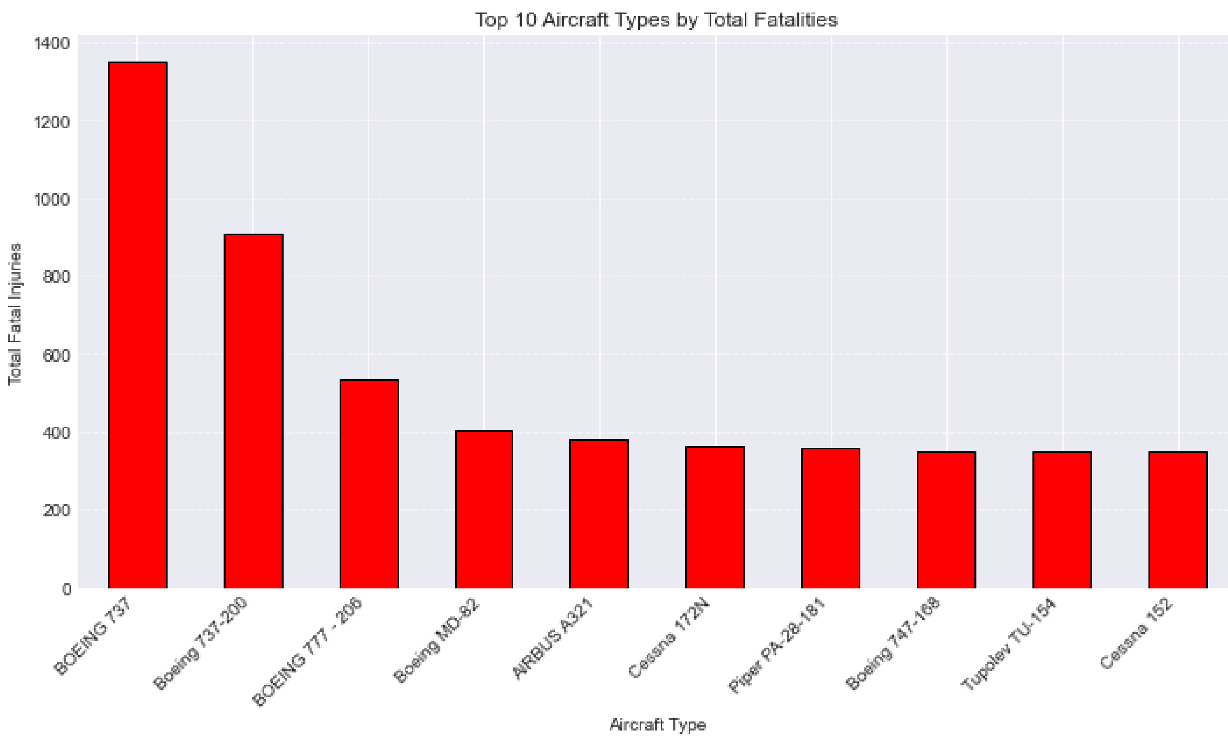


This chart highlights which aircraft have been most frequently involved in accidents. The Cessna 152 and Cessna 172 top the list.

Fatal Injuries Across Aircraft Types

This visualization will use a barchart to compare the distribution of fatal injuries by aircraft types. The chart shows which aircraft types are deadliest based on total fatalities, even if they didn't crash often.

```
# Group by aircraft type and sum fatalities
fatal_df = df.groupby('Aircraft_Type')
['Total_fatal_injuries'].sum().sort_values(ascending = False).head(10)

# Plot
plt.figure(figsize = (10, 6))
fatal_df.plot(kind = 'bar', color = 'red', edgecolor = 'black')
plt.title("Top 10 Aircraft Types by Total Fatalities")
plt.xlabel("Aircraft Type")
plt.ylabel("Total Fatal Injuries")
plt.xticks(rotation = 45, ha = 'right')
plt.grid(axis = 'y', linestyle = '--', alpha = 0.6)
plt.tight_layout()
plt.savefig('Images/Fatalities.png', dpi=300, bbox_inches='tight') #
saves visual to image folder of my project
plt.show()
```

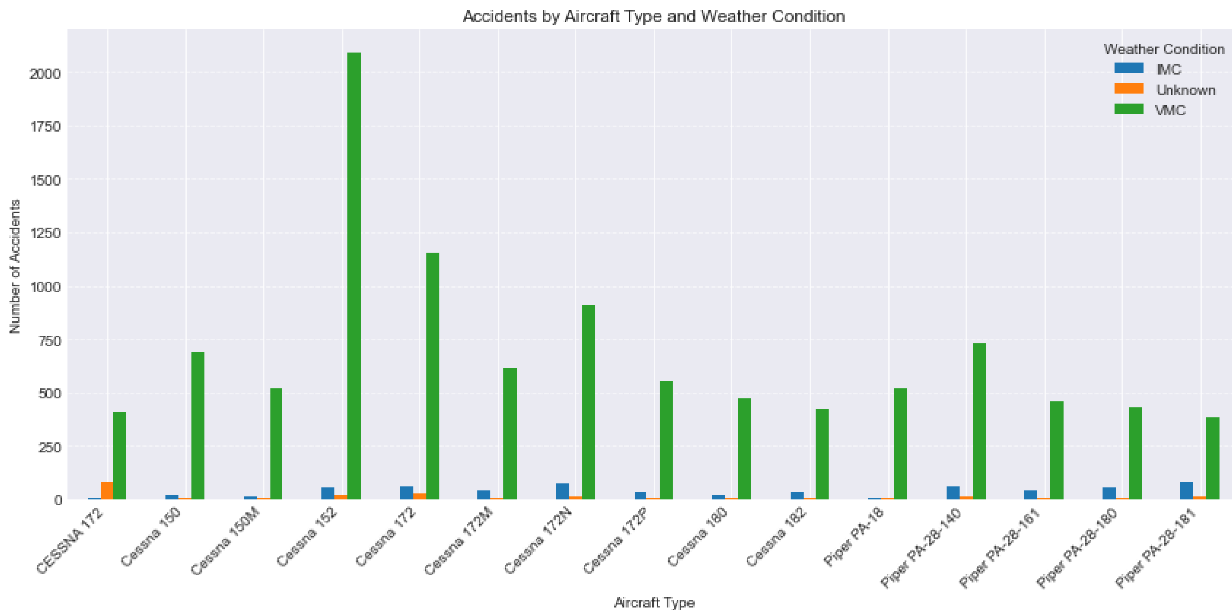


The analysis showed that the Boeing 737 and Boeing 737-200 accounted for the highest number of fatalities across all aircraft types in the dataset.

Impact of Weather

How an external factor weather, affects the accident data. We will create a visualization to show the distribution of accidents by `Weather_condition`.

```
# Get top 15 aircrafts
top_15_aircraft = df['Aircraft_Type'].value_counts().head(15).index
df_top = df[df['Aircraft_Type'].isin(top_15_aircraft)]

# Group and pivot
weather_by_aircraft = df_top.groupby(['Aircraft_Type',
'Weather_condition']).size().unstack(fill_value = 0)

# Plot
weather_by_aircraft.plot(kind = 'bar', figsize = (12, 6))
plt.title('Accidents by Aircraft Type and Weather Condition')
plt.xlabel('Aircraft Type')
plt.ylabel('Number of Accidents')
plt.xticks(rotation = 45, ha = 'right')
plt.legend(title = 'Weather Condition')
plt.tight_layout()
plt.grid(axis = 'y', linestyle = '--', alpha = 0.6)
plt.savefig('Images/Weather.png', dpi=300, bbox_inches='tight') #
saves visual to image folder of my project
plt.show()
```



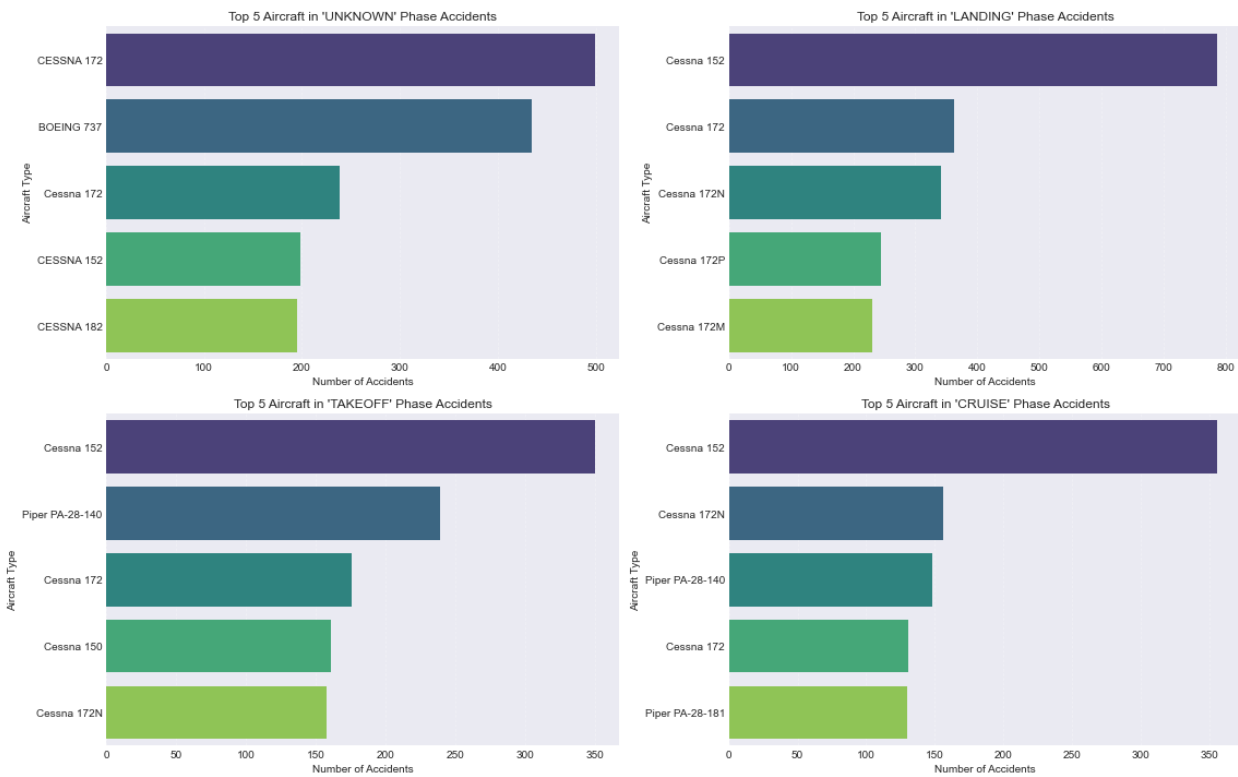
The chart shows that Cessna 152 and Cessna 172 have the highest number of accidents under (VMC).

Accident Distribution by Broad Phase of Flight

Shows which phases of flight like Landing, Takeoff, Cruise are most commonly associated with accidents for each aircraft.

```
# Clean and standardize the phase column
df['Phase_broad'] =
df['Broad_phase_of_flight'].str.upper().str.strip()

# Get the top 4 most common phases
top_phases = df['Phase_broad'].value_counts().head(4).index

# Prepare figure layout
fig, axes = plt.subplots(2, 2, figsize=(16, 10))
axes = axes.flatten()  # Make it easy to iterate over

# Loop over each phase and create individual bar plot
for i, phase in enumerate(top_phases):
    # Filter to only rows for this phase
    df_phase = df[df['Phase_broad'] == phase]

    # Group by aircraft type and count accidents
    top5_aircraft = (df_phase['Aircraft_Type'].value_counts().head(5))

    # Plot
    sns.barplot(x = top5_aircraft.values, y = top5_aircraft.index, ax
= axes[i], palette = 'viridis')

    axes[i].set_title(f"Top 5 Aircraft in '{phase}' Phase Accidents")
```

```
    axes[i].set_xlabel("Number of Accidents")
    axes[i].set_ylabel("Aircraft Type")
    axes[i].grid(axis = 'x', linestyle = '--', alpha = 0.4)

# Adjust layout
plt.tight_layout()
plt.savefig('Images/Flight_phase.png', dpi=300, bbox_inches='tight') # saves visual to image folder of my project
plt.show()
```



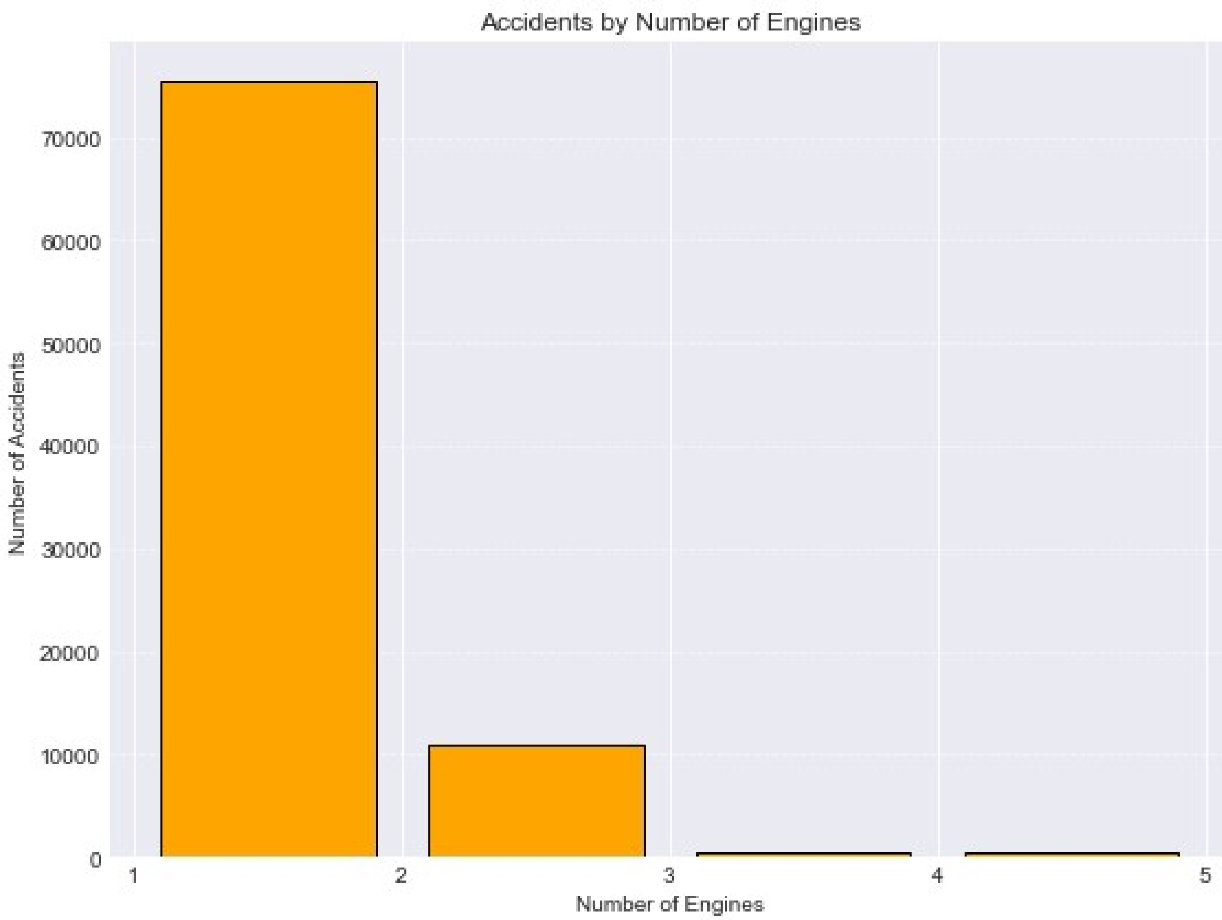
From the barchart above the Cessna 152 records the highest number of accidents during landing, takeoff, and cruise phases. It consistently appears as the leading aircraft involved in accidents across multiple flight stages.

Accidents by Number of Engines

This visualization explores how accident frequency varies based on the number of engines on an aircraft. It provides insight into whether single-engine or multi-engine aircraft are more commonly involved in reported incidents

```
# Plot figure
plt.figure(figsize=(8, 6))

# Use histogram to plot
df['Number_of_engines'].plot(kind = 'hist', bins = range(1, 6), rwidth = 0.8, color = 'orange', edgecolor = 'black')
```

```
plt.title('Accidents by Number of Engines')
plt.xlabel('Number of Engines')
plt.ylabel('Number of Accidents')
plt.grid(axis = 'y', linestyle = '--', alpha = 0.5)
plt.xticks(range(1, 6))
plt.tight_layout()
plt.savefig('Images/engines.png', dpi=300, bbox_inches='tight') #
saves visual to image folder of my project
plt.show()
```



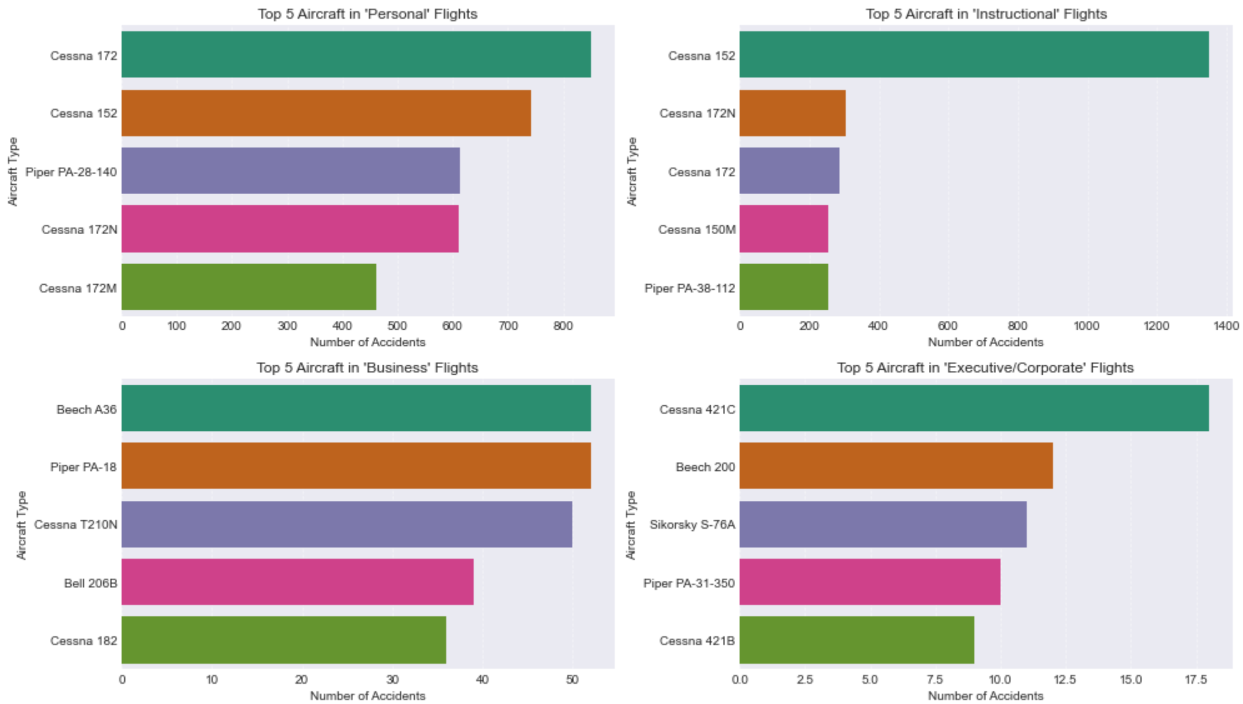
The majority of accidents involved single-engine aircraft, accounting for over 70,000 incidents, while aircraft with two or more engines had significantly fewer accidents.

Aircraft Accident Patterns by Purpose of Flight

This section analyzes accident patterns based on the purpose of flight, focusing on personal, instructional, business, and executive operations.

```
# Clean and standardize purpose of flight column
df['Purpose_clean'] = df['Purpose_of_flight'].str.upper().str.strip()
```

```python
# Define relevant purposes for the company purpose
relevant_purposes = ['PERSONAL', 'INSTRUCTIONAL', 'BUSINESS',
'EXECUTIVE/CORPORATE']

# Filter dataset for relevant purposes
df_relevant = df[df['Purpose_clean'].isin(relevant_purposes)]

# Group by purpose and aircraft type
grouped = df_relevant.groupby(['Purpose_clean',
'Aircraft_Type']).size().reset_index(name = 'Count')

# Get top 5 aircraft for each purpose
top5_per_purpose = (grouped.groupby('Purpose_clean').apply(lambda x:
x.nlargest(5, 'Count'))).reset_index(drop = True))

# Set up plot 2 rows, 2 columns
fig, axes = plt.subplots(2, 2, figsize = (14, 8))
axes = axes.flatten()

# Plot one chart per purpose
for i, purpose in enumerate(relevant_purposes):
    data = top5_per_purpose[top5_per_purpose['Purpose_clean'] ==
purpose]
    sns.barplot(x = 'Count', y = 'Aircraft_Type', data = data, ax =
axes[i], palette = 'Dark2')
    axes[i].set_title(f"Top 5 Aircraft in '{purpose.title()}'
Flights")
    axes[i].set_xlabel("Number of Accidents")
    axes[i].set_ylabel("Aircraft Type")
    axes[i].grid(axis = 'x', linestyle = '--', alpha = 0.5)

# Show
plt.tight_layout()
plt.savefig('Images/flight.png', dpi=300, bbox_inches='tight') # saves
visual to image folder of my project
plt.show()
```



The Cessna 152 and 172, 172N dominate accidents under both Instructional and Personal flight purposes.The Beech A36 and Piper PA-18 are the most involved in accidents during business flights, while the Cessna 421C and Beech 200 appear more frequently in executive or corporate flight accidents

Business Recommendation

1. Accident Trends Over Time (High vs. Low-Risk Aircraft)

Recommendation: Favor the low-incident aircraft for early adoption. Approach high-incident models like the Cessna 152 and 172 with caution—only include them if comprehensive safety training and maintenance frameworks are established.

2. Accidents by Phase of Flight

Recommendation: The takeoff, landing, and cruise phases are the most accident-prone, with the Cessna 152 frequently involved therefore,select aircraft with proven stability and safety during these critical flight phases. Emphasize scenario-based simulation training for pilots to handle real-world challenges during these moments.

3. Fatalities Distribution

Recommendation: While light aircraft have higher accident frequency, Boeing 737 and 737-200 account for the highest number of fatalities per incident due to their large passenger capacity and commercial nature. Therefore, the company should Consider starting with smaller jets to build operational maturity before scaling to larger, high-capacity aircraft.

4. Number of Engines

Recommendation: Single-engine aircraft dominate the accident statistics, indicating higher vulnerability during mechanical failure or adverse flight conditions. For the company entering the aviation sector, especially in commercial sector, it is advisable to prioritize multi-engine aircraft in the initial purchase.

5. Flight Purpose

Cessna 152, 172, 172N dominate accident counts in Instructional and Personal flights.Beech A36 and Piper PA-18 show frequent accidents in business flights.Cessna 421C and Beechcraft 200 are commonly involved in executive or corporate. Based on the analysis, commercial aviation particularly executive and corporate flights has lower accident rates compared to personal and instructional flying.Entering the commercial sector allows the company to build trust, attract premium clients and scale operations more sustainably.

Summary

The analysis of aircraft accident trends, fatality rates, and flight purposes suggests that entering the commercial aviation sector particularly executive and corporate operations is the most strategic and safety aligned choice. High-incident aircraft like the Cessna 152 and 172 should be approached cautiously and the company should prioritize low-incident, multi-engine aircraft with strong safety records, especially during critical phases of flight. To minimize risk and build operational maturity, I advise the company to start with smaller, safer jets, implement scenario-based pilot training, and gradually scale operations positioning itself as a reliable, safety-first aviation provider.